Readiness, Behavior, and Foundational Mathematics Course Success

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Few studies have looked at the impact of specific and observable course behaviors [on academic performance].

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ABSTRACT: ***This study examines the effects of math readiness and student course behavior (e.g., attendance, participation, homework completion) on knowledge gain and course success using two samples of students enrolled in foundational skills (noncredit-bearing) mathematics courses. As hypothesized, entering student mathematics readiness and course behavior predicted posttest mathematics knowledge. Posttest knowledge and course behavior predicted course success (i.e., passing the course). Results highlight the importance of mathematics readiness and student behavior for understanding mathematics knowledge gains and course success. Implications for institutional policy and practice using effective diagnostic testing and behavioral monitoring are discussed.***

First-year student retention and successful course completion is a challenge for postsecondary institutions, particularly community colleges. According to the latest national figures, approximately 45% of degree- or certificate-seeking community college students fail to maintain enrollment or earn a credential (certificate or degree) within the first 2 years of enrollment (Provasnik & Planty, 2008). The longer-term retention and degree-attainment rates are even more concerning: Only 28% of community college students received any type of certificate or degree within 6 years (Provasnik & Planty, 2008). Important factors contributing to low degree attainment are lack of academic preparation for college-level coursework (Strayhorn, 2011) and a lack of student motivation (Rosenbaum, Redline, & Stephan, 2007). For example, based on the ACT College Readiness Benchmarks, which are tied to a 50% likelihood of earning a B or better in credit-bearing college general education courses, only 24% of high school graduates were academically prepared for college in all four core subject areas (ACT, 2010). When considering the ACT Mathematics Benchmark alone, 43% of high school graduates are ready to succeed in college-level mathematics courses. Students who do not have the necessary prerequisite skills and knowledge, or who may not be fully committed to attaining a degree, are less likely to succeed in college courses or to return for a second year (Robbins, Allen, Casillas, Peterson, & Le, 2006).

The primary method for helping students who are underprepared for postsecondary coursework progress toward successful degree attainment is developmental instruction (see Attewell, Lavin, Domina, & Levey, 2006). Due to their open enrollment policies, much of the remediation challenge has fallen to community colleges. Between 2000 and 2008, the percentage of two-year college students taking at least one developmental course to improve their foundational skills rose from 39% to 44% (NCES, 2010). The estimated percentage of students needing remediation tends to be greater in mathematics (70%) than in English (34%; Biswas, 2007).

Course placement is used to put students into courses in which they are able to master material designed to prepare them for eventual successful completion of college algebra (Smith & Michael, 1998). The dilemma involved in setting rigorous course placement standards has been highlighted by Jacobsen (2006), who has pointed out that placing students in noncredit-bearing developmental mathematics courses increased their mastery of the foundational skills needed for college algebra. However, it also has resulted in reduced program completion due to high attrition rates. Bahr (2010) reinforces this point by highlighting the disparities in course completion rates at differing levels of initial math skills. Within developmental mathematics, Bahr's results suggest that student persistence behavior is critical for understanding course completion and success as the math "skill gaps" themselves.

The effectiveness of developmental instruction has been a topic of research for approximately 2 decades (e.g., Bailey, Jeong, & Cho, 2010; Boylan, 2009; Conley, 2007). Specific to developmental math, researchers have tried to better understand which approaches and strategies work best to strengthen adult students' math skills to help them progress into college-level courses (Golfin, Jordan, Hull, & Ruffin, 2005). Promising practices include the use of technology to assess and accurately place students into appropriate-level math courses and tailored instruction as opposed to traditional lecture and lab format.

The potential of the tailored instruction approach was demonstrated by Waycaster (2001), who successfully used individualized computer-aided instruction in developmental math courses at several two-year institutions. Similarly, Quinn (2003) studied a college that used a computer-based placement test to route students into the appropriate courses. Students who did not meet a particular cutoff score were assigned courseware modules to improve their skills and then allowed to take the placement test again. A general conclusion of this line of work has been that effective course placement is essential to success.

In a separate line of research, a variety of primary studies and meta-analyses have demonstrated the importance of psychosocial constructs, including personality, study skills, and other academic behaviors (e.g., time management) to academic performance and persistence in postsecondary settings (Crede & Kuncel, 2008; O'Connor & Paunonen, 2007; Poropat, 2009; Robbins et al., 2004). However, few studies have looked at the impact of specific and observable course behaviors related to psychosocial skills, such as attendance and participation. For example, Dollinger, Matyja, and Huber (2008) examined the extent to which controllable factors such as attendance and study time contribute to college academic performance after controlling for past performance, aptitude, and personality characteristics. Although the best predictors of performance were ability and past performance, study time and attendance were related to performance and explained an additional 6-10% of the variance explained. Similarly, studies by Conard (2006) and Farsides and Woodfield (2003) found that attendance, as an indicator of "application and effort" (Farsides & Woodfield, 2003, p. 1236) predicted academic performance (GPA) above and beyond the effects of intellectual ability and personality characteristics such as conscientiousness. Thus, based on available research, course behavior appears to be an important factor in course success.

Taken together the preceding lines of research suggest that placing students in courses in which they are likely to succeed depends on both entering skill levels and student motivation or effort. Examining these two issues can help shed light on the best ways to improve the success rates of community college students. The premise of the current study is that the combination of effective course placement and behavioral effort factors is essential to successful completion of developmental mathematics courses. We applied the best practices in individualized delivery of developmental math education along with our knowledge of academic behavior (cf. ACT, 2012, Robbins et al., 2004; Robbins, Oh, Le, & Button, 2009) to better understand developmental mathematics course success.

The model tested in this study (shown in Figure 1, p. 16) combines academic skills (entering math skills) and course behavior (instructor-reported effort ratings) measures to predict course success. The model proposes that entering students' mathematics readiness (i.e., initial knowledge) directly predicts later math knowledge (measured via a posttest) which, in turn, is predictive of course success (completing with a passing grade). This model also allows for examination of the extent to which precourse academic skills and student behaviors influence course success separately as well as together. Specifically, math readiness is expected to show a strong direct effect on posttest math knowledge and a strong indirect effect on course success. Course behavior is expected to have direct effects on both math knowledge and course success. Students who expend higher levels of effort are expected to demonstrate higher score gains and success rates than those students who expend less effort.

Method

Demographics

Institution. The study institution is an open admissions two-year public college in a large Midwestern U.S. city serving more than 14,000 students. Based on institutional enrollment data, approximately 70% of the students are part time and 58% are female. A majority of students (47%) are Hispanic, 33% are White, 9% are African American, and 8% are Asian/Pacific Islander. Nearly all participants reside in state, and 47% are age 24 or younger.

Participants. A total of 1,254 students were enrolled in developmental mathematics courses at the study institution during the Fall 2008 (N = 819) and Spring 2009 (N = 435) semesters. These students were enrolled in developmental courses because they did not have the skills required for success in credit-bearing courses based on the results of a computer-adaptive placement test (COMPASS). COMPASS provides reliable and valid measures of current mathematics skill levels and instructional needs (ACT, 2006). Students were placed into a mathematics tier based on COMPASS placement test scores. Only new students were used in the study; spring students who had enrolled in a developmental mathematics course in the previous fall were removed.

Participant demographics are shown, by semester, in Table 1. Demographics are shown for the entire starting sample of participants for each semester, as well as for the subset that achieved course success. Average student age ranged from 21 to 23 across samples (SD = 6 years) and students were predominantly female and Hispanic. Demographics are very similar for the samples of

Table 1

Demographics for the Fall 2008 and Spring 2009 Semesters

	Fall 2008		Spring 2009	
Demographics	**Started course (N=819)**	**Completed course (N=507)**	**Started course (N=435)**	**Completed course (N=231)**
Age	M=21.1	M=21.2	M=22.6	M=23.1
	SD=5.9	SD=6.3	SD=6.3	SD=6.2
Gender				
Female	59.4	60.3	54.5	55.9
Male	40.6	39.7	45.5	44.1
Ethnicity				
Asian	5.6	8.0	6.4	8.0
Black	13.3	10.2	15.7	12.9
Hispanic	57.5	59.1	56.7	57.1
Native American	0.5	0.2	0.0	0.0
Other	0.4	0.5	1.1	1.8
White	22.7	21.9	20.0	20.3

students who began the course and the subsets that completed the course successfully.

Predictor Variables

Mathematics readiness. The COMPASS mathematics diagnostic tests were administered to measure students' strengths and weaknesses in specific mathematics content areas. For each of two developmental mathematics courses, six diagnostic pretests were administered for content areas mapped to the course content. The prealgebra diagnostics include operations with integers, fractions, and decimals; positive integer exponents; square roots and scientific notation; ratios and proportions; as well as percentages and averages. The algebra diagnostics include substituting values into algebraic expressions; setting up equations; operations and factoring of polynomials, exponents, and radicals; rational expressions; and linear equations.

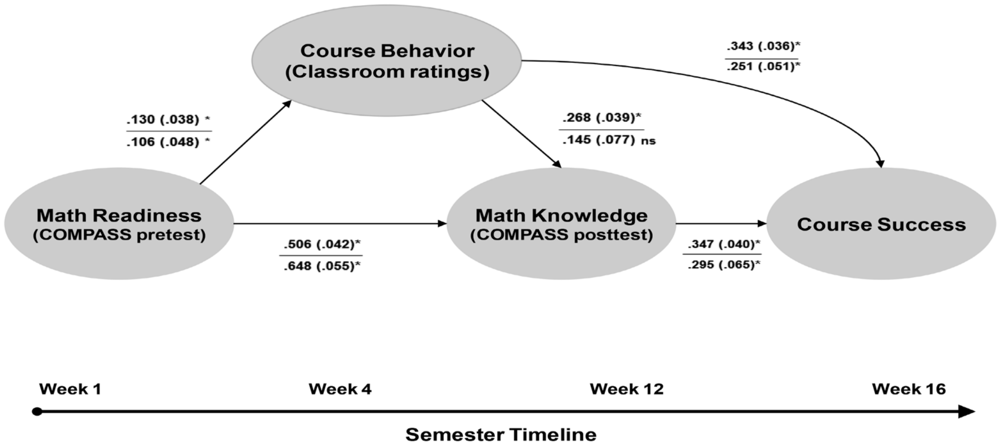

Figure 1. **Proposed and tested model for combining cognitive and behavior measures to predict course success.**

Note. Fall 2008 coefficients are above the line; Spring 2009 coefficients are below the line.

* Significant paths are 2 *SE*s from zero; ns = nonsignificant paths.

Because the diagnostic tests are adaptive, traditional measures of internal consistency reliability are not applicable. Instead, the marginal reliability coefficient is used to report reliability. Based on this measure of reliability, the COMPASS diagnostic scales have internal consistency reliability ranging from .84 to .92, with a median of .85. Each diagnostic test score is an estimate of the percentage of test items the student would answer correctly if they were administered all items in the COMPASS item pool in that content area. Because each diagnostic measure uses the same scale, an aggregate measure of initial mathematics readiness level is defined as the mean of the six diagnostic scores.

Student course behavior. During the developmental mathematics courses, instructors rated students' levels of participation, attendance, and completion of homework assignments. A 5-point rating scale ranging from 1 (almost never) to 5 (always) was used to rate the following four items:

- active participation in group work (student is actively engaged during group work; helps other students with assignments; does his/her fair share of the work, etc.),
- active participation in lecture (student is alert and attentive during class: asks/answers questions: etc.),
- attendance (student attends class: stays for whole period, etc.), and
- completion of homework assignments (student completes assignments thoroughly and completely; turns assignments in on time).

These items were combined into a composite rating of student course-behavioral effort. Internal consistency of this composite was .92 using Cronbach's coefficient alpha, suggesting that these behaviors were tapping the same construct. Since students in each course section were rated by a single instructor, it was not possible to calculate interrater agreement of behavioral effort ratings.

However, research on course behavioral ratings suggests that these types of scales can be used reliably by single raters (Das, Frost, &, Barnowe, 1979; Grussing, Valuck, & Williams, 1994). Further, the research suggests that behavioral ratings are related to performance in both academic and work settings, including course grades and other indicators of academic achievement (ACT, 2012; Knapp, Campbell, Borman, Pulakos, & Hanson, 2001; Motowidlo & Borman, 1977).

Dependent Variables

Mathematics knowledge. The COMPASS diagnostic tests administered at the beginning of the course were readministered during the 12th week of the semester to measure mathematics knowledge gain. The reliability estimates for the diagnostic tests, as well as how the six scores were combined to form a composite, remained as previously described for the measure of initial mathematics readiness. Controlling for initial mathematics readiness allows for measurement of the effect of course behavior on growth in mathematics knowledge (Wright, Sanders, & Rivers, 2006). Within this model of course success, posttest mathematics knowledge was treated as an intermediate rather than a final outcome.

Course success. As with most developmental mathematics courses, the developmental courses at the study institution were competency based. Students who successfully complete all required examinations and homework received a passing grade. For the purposes of this study, a dichotomous variable of course success was used that was based on pass/fail grades assigned by course instructors. Students who dropped out were coded as failures as were the students who remained in the course but received a failing grade. Course success was defined as both staying enrolled and passing the course.

Procedures and Instructor Training

Students placed into the developmental mathematics (noncredit-bearing) courses completed COMPASS diagnostic tests during the first week of classes to provide a deeper assessment of initial skill levels in prealgebra and algebra. Instructors and students were provided pretest diagnostic results. Individual student action plans were created and reviewed with each student, and lesson plans and homework assignments were tailored to a modal class profile of diagnostic strengths and weaknesses. Instruction focused more on content in which students scored low and less on content in which students scored high.

Instructors rated students' behavioral effort in the course during week 4 of classes after instructors had become familiar with students and their work habits. During week 12 of the semester, students were then readministered the COMPASS diagnostics tests to assess knowledge gains. As with pretest results, students and instructors were provided COMPASS diagnostic posttest reports so that individual scores could be compared to target achievement goals. Weaker content areas were targeted for additional in-course review. At the end of the semester (week 16), instructors assigned grades based on students' performance in the developmental courses.

Training for instructors on how to rate students was provided via written materials and, for

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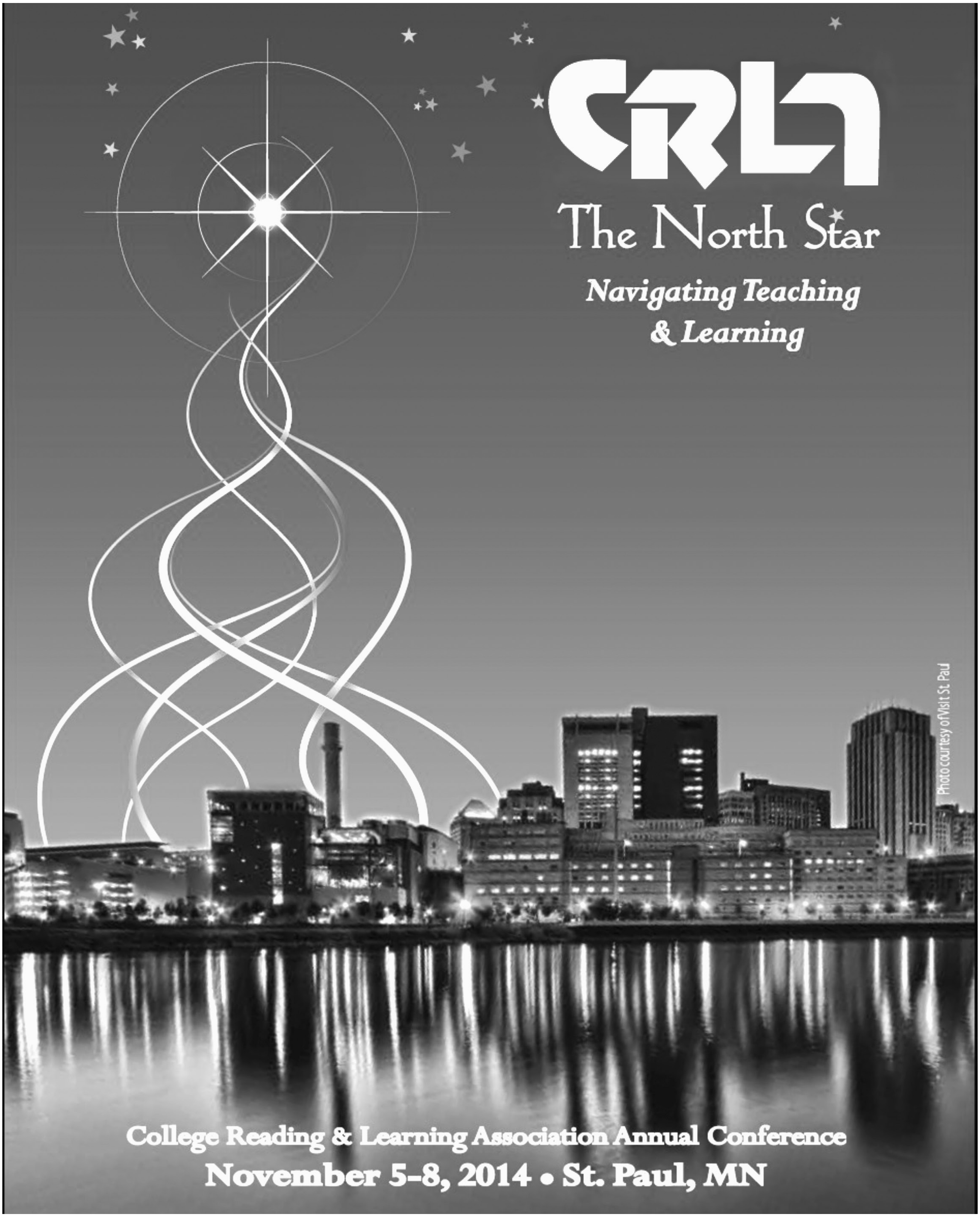
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those who requested it, in person. Despite these efforts, some instructors did not follow through with the ratings even after expressing initial commitment to the study and after multiple reminders.

Analytic Methods

The analyses were based on four variables: initial mathematics readiness, course behavior, mathematics knowledge, and course success. Course behavior and mathematics knowledge (COMPASS posttest) data were missing when students withdrew and where instructors did not follow through in rating students' course behavior. In addition, students who had poor attendance were less likely to take the COMPASS posttest. Instead of removing these students from the analyses altogether, a method for estimating path coefficients from the correlation matrix of the dependent and independent variables was used (see Wright, Sanders, & Rivers, 2006). This approach allowed students with valid data for the two variables forming a path to be included in that path's coefficient estimation, even if they were missing other variables in the model that were not part of the estimated path.

The path coefficients can be interpreted as standardized regression weights where ß is the change in Y given a one standard deviation change in X. Standard errors (SEs) for the coefficients were calculated using bootstrap estimation. Path coefficients greater than two SEs from zero are considered statistically significant ($p < 0.05$).

To cross-validate the model, data for fall and spring semesters were analyzed separately. Within each semester, two general types of developmental math courses were included: prealgebra and algebra. Data from the two course types were pooled. To estimate each path coefficient, an indicator for course type was used as a covariate to eliminate confounding associated with course type.

Results

Testing the Proposed Path Model

Table 2 summarizes the direct, indirect, and total effects of each variable in the path model on three outcomes: course success, posttest math knowledge, and course behavior ratings. Figure 1 (p. 16) illustrates the same results in a path diagram. Although course success is the primary outcome of interest, the prediction of the other two outcomes (using math readiness) can help in explaining the effects on this primary outcome. Results are reported by semester and the statistically significant coefficients are marked by an asterisk in Table 2 and Figure 1.

Fall semester effects. The path coefficients for posttest math knowledge (ß = .347) and course behavior (ß = .343) suggested that these variables had fairly strong direct effects on course success. Course-behavior ratings also had a moderately strong direct effect on posttest math knowledge (ß = .268), thus the indirect effect of course behavior on course success (ß = .093) was significant, reinforcing the importance of course behavior on both knowledge gain and course success. Due to its strong direct effect on posttest math knowledge (ß = .506) and smaller effect on course behavior (ß = .130), math readiness had a moderate indirect effect on course success (ß = .232). In other words, mathematics readiness (pretest) impacted later mathematics knowledge (posttest) and course behavior, which in turn affected course outcome. The overall effect of posttest math knowledge and course behavior on course success was strong, with a resulting model Multiple *R* of 0.53.

Spring semester effects. The pattern of direct and indirect effects on spring course success was similar to the fall semester. Posttest math knowledge (ß = .295) and course behavior (ß = .251) again had moderately strong direct effects on course success. The total effect of course behavior on course success (ß = .294) was just slightly larger than its direct effect. Math readiness had a moderate indirect effect on course success (ß = .222) which was again likely due to its strong direct effect on posttest math knowledge (ß = .662) and smaller effect on course behavior (ß = .106).

The spring results differed from the fall in that course behavior did not have a significant direct effect on posttest math knowledge (ß = .145, SE=.077). The overall effect of posttest math knowledge and course behavior on course success was strong, with a resulting model Multiple *R* of 0.41. However, it was noticeably smaller than *R* for the fall semester sample.

Table 2

Estimates of Effects on Path Outcomes

	Fall semester		Spring semester	
Outcome and effect	**Effect**	***SE***	**Effect**	***SE***
Course behavior				
Direct				
Math readiness	.130*	.038	.106*	.048
Posttest math knowledge				
Direct				
Course behavior	.268*	.039	.145	.077
Math readiness	.506*	.042	.648*	.055
Indirect				
Math readiness	.035*	.011	.014	.010
Total				
Math readiness	.541*	.041	.662*	.054
Course success				
Direct				
Posttest math knowledge	.347*	.040	.295*	.065
Course behavior	.343*	.036	.251*	.051
Indirect				
Course behavior	.093*	.016	.042	.025
Math readiness	.232*	.028	.222*	.047
Total				
Course behavior	.435*	.029	.294*	.047

* Denotes statistically significant coefficients (at two or more standard errors from the mean).

Overall effects. Overall, the structural model results confirmed expectations that students' entering math skills and behavioral effort have direct and indirect effects on course success. The pattern of direct, indirect, and total effects on course success was similar across semesters, with one exception. The direct effect of course behavior on posttest math knowledge and its indirect effect on course success was significant in the fall but not in the spring. Some possibilities are addressed for this inconsistency in the discussion.

In general, both math readiness and course behavior were useful predictors of posttest math knowledge with math readiness being the strongest predictor. Not surprisingly, the math knowledge learned by week 12 of the semester was predictive of eventual course success. Course behavior had consistent and sizeable direct effects. Descriptive statistics and correlation matrices used to generate path coefficients for each sample are included in the Appendix.

Another View of the Effects on Knowledge Gains and Course Success

In addition to the path models, we examined the effects of math readiness and course behavior on knowledge gains and course success by classifying students by level of behavior. To examine knowledge gains by effort level, students' course-behavior ratings were split into three levels: low (bottom 25th percentile), medium (middle 50th percentile), and high (top 25th percentile). Next, student knowledge gain was compared by effort level. Not surprisingly, students who were rated by their instructors as demonstrating a higher level of effort during the course made larger gains in math knowledge. During the fall semester, students achieved the following mean gains in math knowledge (as measured by COMPASS) when sorted on course behavior ratings: 7.1 (low effort), 10.6 (medium effort), and 15.9 (high effort). During the spring semester students achieved the following mean gains when sorted based on course behavior: 8.9 (low), 10.0 (medium), and 11.9 (high). These gain patterns are another way to demonstrate that effort (e.g., attend class, complete homework, participate in discussion) is related to learning.

We also examined course success rates by students' math readiness and instructors' average course-behavior ratings. Table 3 presents fall semester success rates and Table 4 presents spring semester success rates. Each table shows students sorted into three levels of math readiness (low, medium, high) as well as three levels of course-behavior rating (low, medium, high). Similar to the mean gains previously presented, Tables 3 and 4 show substantial differences in course success rates by course behavior, both by the three overall behavior levels as well as by behavior within each readiness level.

As can be seen, students at all math readiness levels are more likely to do well if they engage in appropriate classroom and homework activities, whereas those students who do not exert sufficient effort have lower probabilities of success. In particular, those students at the lower end of the readiness spectrum and who demonstrate low effort are at high risk for failure. Indeed, only 19% of students in this category completed the course successfully in the fall and 10% completed the course successfully in the spring.

Discussion

The effects of math readiness and course behavior on course success were examined using a sample of students enrolled in developmental mathematics courses. Specifically, this model combined academic skills (math readiness) and academic behavior (in-class behavior ratings) to predict course success. Results from this study reinforce the importance of understanding the combination of academic skills and student effort on developmental course success. Math readiness showed strong direct effects on posttest math knowledge as well as indirect effects on course success via course behavior. Posttest math knowledge also showed strong direct effects on course success. Further, student course behavior showed a strong direct effect on course success, as well as indirect effects through posttest math knowledge. Across both semesters, the model results confirmed our expectations that students' entering math readiness and course behavior have direct and indirect effects on course success.

Although the model estimates were mostly consistent across the two semesters, there were some differences that may not be completely due to chance. The overall model fit for predicting course success was larger for fall (R=0.53) than for spring (R=0.41). The spring sample was a mixture of new enrollees and students who enrolled in the fall but took the developmental math course in the spring. The two samples were quite similar in terms of demographics and mean math readiness, but more students experienced course success in the fall (62%) than in the spring (53%).

Differences in the success rates and differences in the model results might be related to factors associated with fall and spring enrollment. One hypothesis is that spring enrollees are more likely to have delayed enrollment for reasons that also cause them to have additional challenges to course success (e.g., competing priorities such as family obligations and needing to work more hours). This hypothesis is supported by prior research that has shown that delayed enrollment is related to lower odds of degree completion (even after controlling for achievement, socioeconomic factors, and high school completion)

Table 3

Success Rates for Fall 2008 Based on Math Readiness and Course Behavior

	Effort level (course behavior)		
Math readiness	**High**	**Medium**	**Low**
High	.92	.80	.59
Medium	.86	.67	.29
Low	.74	.50	.19

Note. N = 713.

Table 4

Success Rates for Spring 2009 Based on Math Readiness and Course Behavior

	Effort level (course behavior)		
Math readiness	**High**	**Medium**	**Low**
High	.83	.65	.50
Medium	.68	.51	.30
Low	.64	.43	.10

Note. N = 304.

and that delayed enrollees are more likely to transition to other life roles such as spouses or parents before entering college (Bozick & DeLuca, 2005).

The findings of this study generally demonstrate that better course behavior was predictive of larger knowledge gains. Further, higher course-behavior ratings were also associated with a much greater likelihood of course success (defined as remaining enrolled and passing the course). In other words, as important as diagnostic assessment and effective course placement is to knowledge gain and academic mastery, a student's willingness to do the work is essential for learning and course success. Although this is an intuitive finding, it is not clear that institutions are successfully addressing both issues (academic skill and student behavior deficits) as part of their core mission of classroom instruction. Our findings suggest that a two-pronged approach to address both issues is necessary for students to succeed in developmental courses.

Study findings indicate that behavioral components are critical to the academic mastery and persistence that culminate in degree attainment. Further, it is evident that "hybrid" interventions are effective in helping students to succeed in post-secondary studies (cf. Robbins et al., 2009). Hybrid interventions are those involving a combination of assistance with academic skills content (e.g., prealgebra and algebra skills in a developmental mathematics course) as well as assistance in developing effective academic behaviors (e.g., goal setting, time management, working productively with peers and instructors, regulating affect and behavior, etc.). It is also evident that when students at risk are (a) identified on a timely basis, (b) provided interventions to address their needs, and (c) make even mild-to-moderate use of the prescribed interventions, they benefit with increased GPA and persistence in enrollment (Robbins et al., 2009). The model being developed at the study institution contains the components necessary to continue to examine the use and effectiveness of hybrid interventions in community colleges.

Limitations

The study used a well-defined path model that was tested for 2 semesters, which allowed assessment of the model's consistency and reduced potential problems related to sampling error. However, the sampling error issue is illustrated by the differences in path coefficients from instructor-reported behavior to posttest results for the fall and spring samples. This difference may be due to chance or to variations in the samples associated with spring and fall-enrolled developmental math students. Including data from subsequent semesters would allow even more robust estimates and minimize the possibility that conclusions are due to sampling error.

In addition, this study was based only on developmental mathematics courses. Replicating these findings across more academic areas considered essential for college readiness and success (e.g., English and science) would lend further credence to the model. Also, this research is limited to students from one institution; conducting this work at multiple institutions (preferably from different geographical regions) would strengthen the generalizability of the results. Further, as noted in the methods section, despite attempts to provide instructors with training on assigning behavioral ratings, some instructors did not follow through with the ratings. We looked at institutional records to see if this issue may have impacted our results in any systematic way and found that students enrolling in different sessions (i.e., different instructors) of the same course showed similar retention, course success rates, and behavioral patterns. Thus, we believe that the student effort distributions from the missing cases would resemble those we included in this paper. Based on this information, we do not believe that missing ratings had a systematic impact on our findings.

Behavioral components are critical to academic mastery and persistence.

A final limitation of the study is caused by missing data associated with course failure: Because students with lower effort and poor attendance were less likely to take the COMPASS posttest, it is possible that our estimates of the direct effect of posttest knowledge on course success are biased.

Implications for Practice

Our findings provide an initial step to empirically support the assessment and intervention model that is being developed at the study institution. In this model, each new student is assessed from both academic and behavioral risk perspectives and subsequently referred to resources for academic and behavioral skill development. The diagnostic score profiles help faculty and students to better understand areas of strength and need in mathematics content areas. These profiles can be used to more effectively target instruction and intervention both at the individual and classroom levels. Not all students require remediation in all content areas. Thus, helping instructors and students target class modal and individual profiles is likely to improve student learning as well as student motivation and engagement. Using timely and individualized information about specific skills may make the course seem more approachable, thus increasing students' sense of mastery, which in turn is related to increased motivation and engagement (e.g., Hsieh, Sullivan, & Guerra, 2007; Rosenbaum et al., 2007; Senko, Hulleman, & Harackiewicz, 2011).

For example, institutions making use of this information could arrange course sections based on students' profiles so that those students with similar needs (e.g., difficulty with prealgebra concepts) could be grouped together and provided with additional instructional time designed to address their specific skill deficit. This grouping could also be done by instructors so that instruction time and/or content modules can be organized to address the topics that most students find challenging. In addition, institutions and instructors could use students' profiles to match students with strengths in certain content areas with those who have deficits in those same areas as part of a tutoring program. Such a program may have the added benefit of helping to strengthen students' social connectedness within the academic context, which previous research shows is related to persistence in degree attainment (e.g., Robbins et al., 2006). Finally, students' profile information can help to provide a clearer picture to students about their specific skills relative to what they need to know to be successful in future courses and keep them better appraised of their progress toward degree completion.

Institutions could apply the same principles of diagnostic testing and differentiated instruction of academic needs to address students' behavioral needs, such as time management and organizational skills, self-discipline, study habits, communication skills, working in teams, and building resilience when faced with challenges. The potential positive impact of behavioral assessment is driven to some extent by the strength of predictive relationship between assessed behaviors and college outcomes. It is driven even more so by improvements in behavioral intervention programs that can result from the assessment such as those that address engagement, study skills, and academic motivation (Allen, Robbins, & Sawyer, 2010). For example, students often arrive in college with the goal to major in a particular field without concrete strategies for how to successfully achieve that goal. Community colleges may need to help students develop such strategies, including creating schedules, keeping assignments and priorities well-organized despite competing demands related to work and family, making time to periodically meet with instructors regarding coursework, constantly improving study skills, developing strategies for dealing with obstacles that may come along, and knowing what resources are available (e.g., academic advising, career center, wellness programs, etc.) to make use of them when needed. These topics are often part of an onboarding or first-year experience short course at many four-year colleges. Given the behavioral

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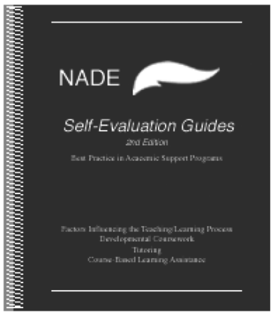

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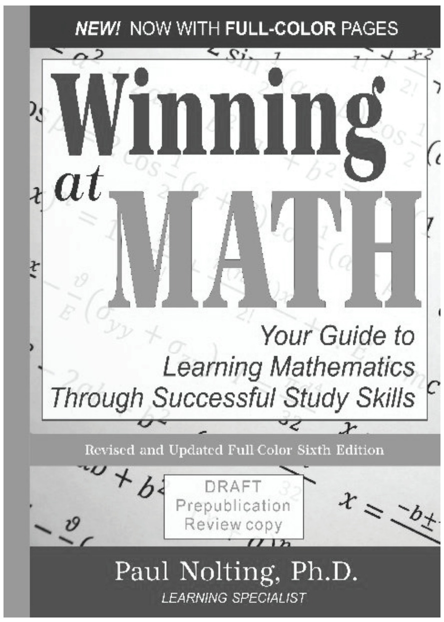

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Written by learning specialist Dr. Paul Nolting, the sixth, research-based edition of *Winning at Math* is the most comprehensive version of the book to date. In addition to the time-tested study strategies featured in older editions, the new *Winning at Math* also includes math-specific study skills custom designed for students taking online and Emporium model courses.

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needs of college students in general, such courses may resonate with students at community colleges. Thus, institutions must have tight alignment between assessment and behavioral intervention just as they must have alignment between academic assessment and instructional programs. In fact, institutions that have created a crosswalk between students' behavioral needs and available campus resources and that explicitly raise students' awareness of such resources via email communications, advising sessions, and early warning systems have found that (a) students are more likely to use available resources, and (b) they experience direct and measurable benefits in the form of increased academic performance and persistence in enrollment from one semester to the next (e.g., Robbins et al., 2009; Tampke & Casillas, 2011).

Implications for Future Research

This study serves as an important first step in evaluating the impact of individualized assessment and instruction for community college students. Future research needs to more carefully control and evaluate model components, as well as expand the model to include interventions. Specifically, future work can concentrate on capturing students' perceptions of services as well as actual service use patterns at community colleges. Such research is essential to gain a better understanding of (a) how students decide to pursue service referrals after their needs have been identified by the institution, (b) which services facilitate the most effective outcomes, and (c) which students benefit the most from said services. The findings from this study suggest that a joint focus on academic skills and academic behaviors is imperative for students to experience success in developmental courses. However, it would also be interesting to examine whether a similar model is effective for a broader range of entry-level courses (e.g., mainstream, introductory English and science, certification programs, etc.).

Conclusion

The current study integrated approaches (academic skills used for course placement and ratings of course behavior) typically used in different lines of research to better understand students' success in developmental math courses. Study findings are consistent with previous literature in that academic skills (e.g., Bahr, 2010) and course behavior (e.g., Farsides & Woodfiled, 2003) are both important to successful completion of developmental mathematics courses. However, to our knowledge, this is among the first studies to examine the interconnected roles of academic skills and effort for predicting student performance in developmental courses. These findings underscore the need for institutions to take a multifaceted approach to assessing and identifying student academic and behavioral skill gaps, and, in turn, provide resources designed to address these gaps. For students, this approach has the potential to provide more customized instruction and feedback based on their specific needs, thus leading to higher rates of successful course completion and degree attainment. For institutions, this approach has the potential to contribute to a tighter alignment between classroom instruction and support services, thus supporting institutions' ultimate purpose of helping individuals achieve their educational goals. In order to move away from a "one-size-fits-all" approach to instruction, service delivery, and student success in educational systems, it seems essential to develop a fuller understanding of the skills (whether based on academic content areas or behavior) that lead to student persistence and success.

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Appendix

Table A1. *Descriptive Statistics and Intercorrelation Matrix for Fall 2008 Sample*

Variable	*N*	*M*	*SD*	1	2	3	4
1. Math readiness	724	28.9	7.7	—	—	—	—
2. Posttest math knowledge	436	41.7	12.1	.52	—	—	—
3. Course behavior	800	14.0	4.8	.13	.33	—	—
4. Course success	819	0.6	0.5	.30	.45	.46	—

Table A2. *Descriptive Statistics and Intercorrelation Matrix for Spring 2009 Sample*

Variable	*N*	*M*	*SD*	1	2	3	4
1. Math readiness	363	32.3	10.2	—	—	—	—
2. Posttest math knowledge	195	40.0	13.4	.67	—	—	—
3. Course behavior	370	15.2	4.7	.12	.22	—	—
4. Course success	435	0.5	0.5	.19	.34	.30	—

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When reasoning through an issue, one should concentrate on the most important information (relevant to the issue) and take into account the most important ideas or concepts. It is easy to forget that, though many ideas may be relevant to an issue, they may not be equally important. Similarly, a thinker may fail to ask the most important questions and instead become mired in superficial questions, questions of little weight. In college, for example, few students focus on important questions such as, "What does it mean to be an educated person? What do I need to do to become educated?" Instead, students tend to ask questions such as, "What do I need to do to get an 'A' in this course? How many pages does this paper have to be? What do I have to do to satisfy this professor?"

Thinking can be more or less significant. It can focus on what is most substantive, what is of the highest consequence, what has the most important implications; or it can focus on the trivial and superficial. Questions that focus on significance include:

- What is the most significant information needed to address this issue?
- How is that fact important in context?
- Which of these questions is the most significant?
- Which of these ideas or concepts is the most important?

Fairness: free from bias, dishonesty, favoritism, selfish-interest, deception or injustice.

Humans naturally think from a personal perspective, from a point of view that tends to privilege their position. Fairness implies the treating of all relevant viewpoints alike without reference to one's own feelings or interests. Because everyone tends to be biased in favor of their own viewpoint, it is important to keep the intellectual standard of fairness at the forefront of thinking. This is especially important when the situation may call on us to examine things that are difficult to see or give something up we would rather hold onto.

Thinking can be more or less fair. Whenever more than one point of view is relevant to the situation or in the context, the thinker is obligated to consider those relevant viewpoints in good faith. To determine the relevant points of view, look to the question at issue. Questions that focus on fairness include:

- Does a particular group have some vested interest in this issue that causes them to distort other relevant viewpoints?
- Am I sympathetically representing the viewpoints of others?
- Is the problem addressed in a fair manner, or is personal vested interest interfering with considering the problem from alternative viewpoints?
- Are concepts being used justifiably (by this or that group)? Or is some group using concepts unfairly in order to manipulate (and thereby maintain power, control, etc.)?
- Are these laws justifiable and ethical, or do they violate someone's rights?

Closing

In this column we have explicated nine essential intellectual standards. In the next column, the third in this series, we briefly analyze the concept of *intellectual standards* as an intellectual construct. We will also elaborate the important understanding that, though standards are prevalent in everyday life, such standards are not always "intellectual" in nature.

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Concluding Remarks

Improving student success in postsecondary basic mathematics is a focus for instructors and administrators alike for reasons ranging from better comprehension in class to better retention on campus. Simplified presentation of material in developmental mathematics classes, though surely requiring more study, shows early promise in satisfying both groups.

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